Spectral Indices
Meaning and interpretation in the space and time domain (time series)

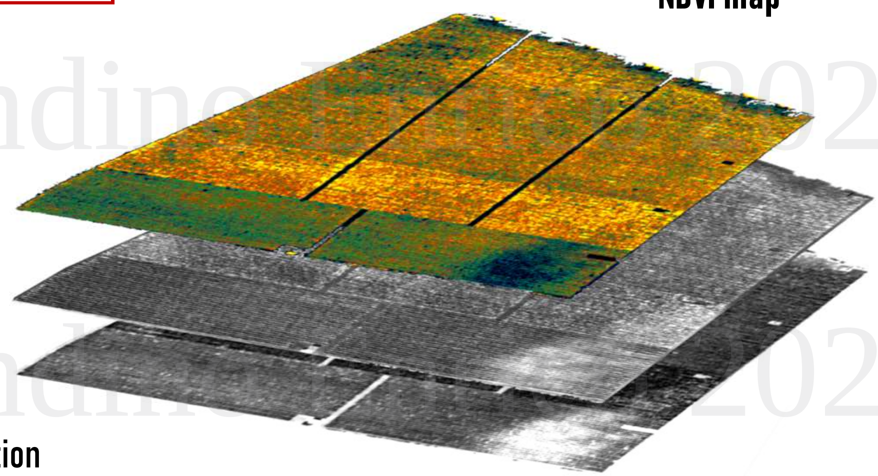
WORKING WITH XS IMAGERY
SPECTRAL INDICES

ONCE IMAGES HAVE BEEN CALIBRATED (i.e. DN converted to the at-the-ground reflectance values) in some applications, it can be preferable to synthesize the spectral content of the whole spectral signature (typically more than 6 bands) focusing on a limited number of bands.
Bands of interest can be combined along mathematical formulas whose meaning can be directly related to the surface feature of interest (vegegative activity, water content, snow state,etc.). Formulas relating bands of a XS image to generate a synthetic information for a specific application are called **SPECTRAL INDICES**. They are computed at PIXEL LEVEL generating new raster layers containing the result of the formula obtained with the local values of the involved bands..

Spectral Index = $f(b_1, b_2, \ldots, b_n)$

NORMALIZED DIFFERENCE VEGETATION INDEX – NDVI

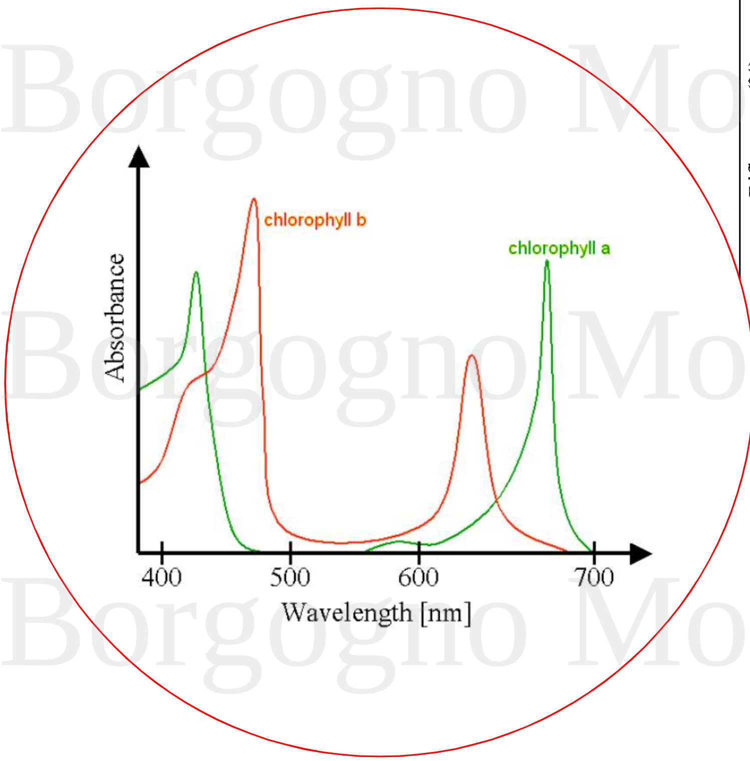
$$NDVI = \frac{NIR - RED}{NIR + RED}$$

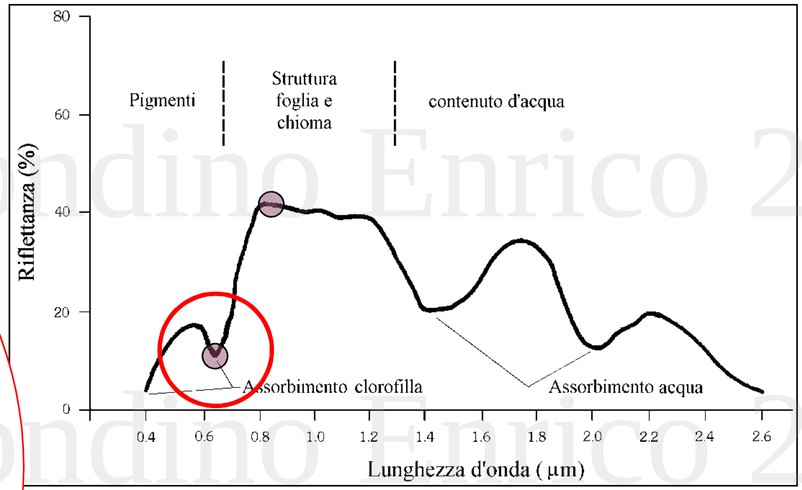


There are many proposed SPECTRAL INDICES, depending on application

Normalized Difference Vegetation Index

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$





NDVI is related to vegetation vigour.

It ranges between -1 and +1. Values higher than 0.4 indicate vegetated pixels.

Higher the value, higher the vigour/biomass.

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SPECTRAL INDICES FOR VEGETATION

Normalized Difference RedEdge Index, NDRE

$$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge}$$

The red edge is the part of the spectrum centred around 715 nm (S2 band 5 or 6) .

Enhanced Vegetation Index, EVI

$$EVI = 2.5 \cdot \frac{NIR - RED}{NIR + 6 \cdot RED - 7.5 \cdot BLUE + 1}$$

Differently from NDVI, EVI is a vegetation index optimized for highly vegetated areas:.

Soil Adjusted Vegetation Index, SAVI

$$SAVI = (1 + L) \cdot \frac{NIR - RED}{NIR + RED + L}$$

SAVI is a vegetation index that takes into account bares soil background, using the empirical factor L to tune reflectances according to cover type hosting vegetation. L ranges between -0.9 and +1.6. Higher the vegetation cover, lower L value.

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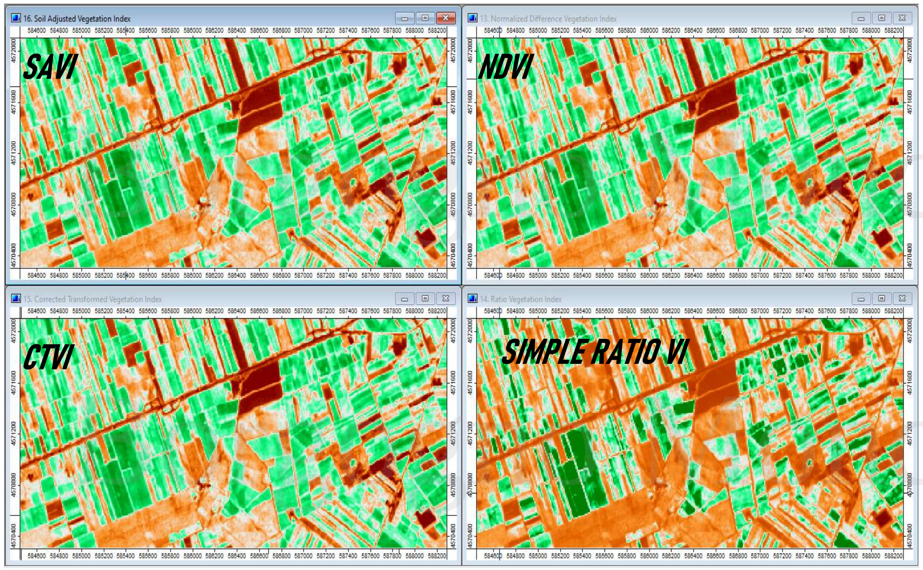
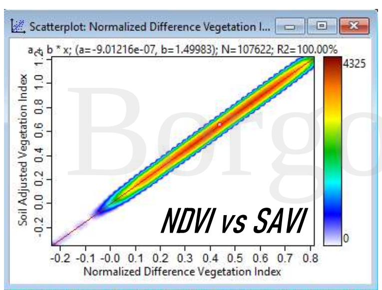
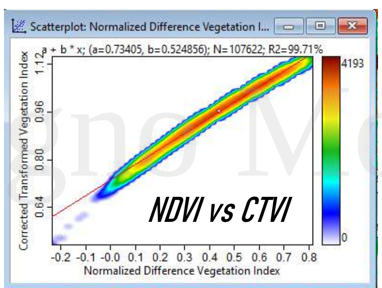
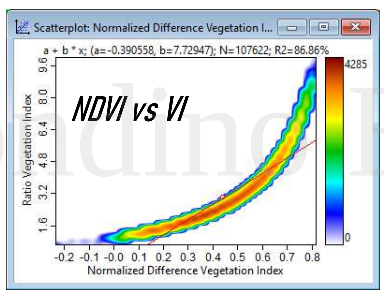
SPECTRAL INDICES FOR VEGETATION



The most of spectral indices aimed at synthesizing similar properties of surfaces are highly correlated in spite of any literature fostering.

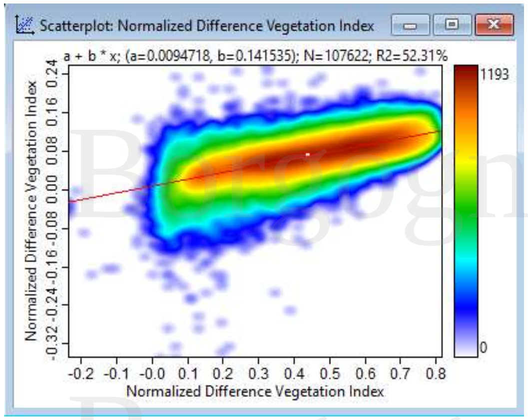






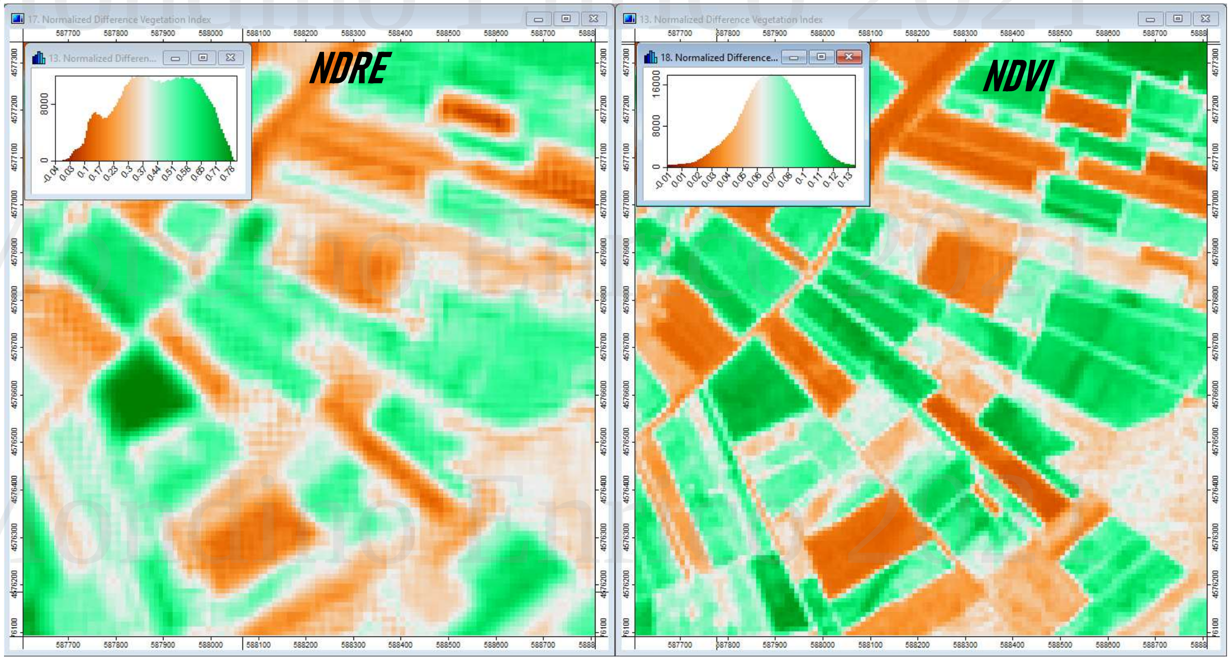
SPECTRAL INDICES FOR VEGETATION

NDVI vs NDRE



NDRE provides a measurement that is able to catch information about a deeper layer of vegetation giving a better insight at permanent or later stages of crops, being Red Edge wavelength able to better penetrate down into the canopy.

NDRE is said to be also less sensitive to saturation related to dense vegetation. Consequently, NDRE can sometimes provide a better measurement of variability in an area that NDVI would see as uniform.



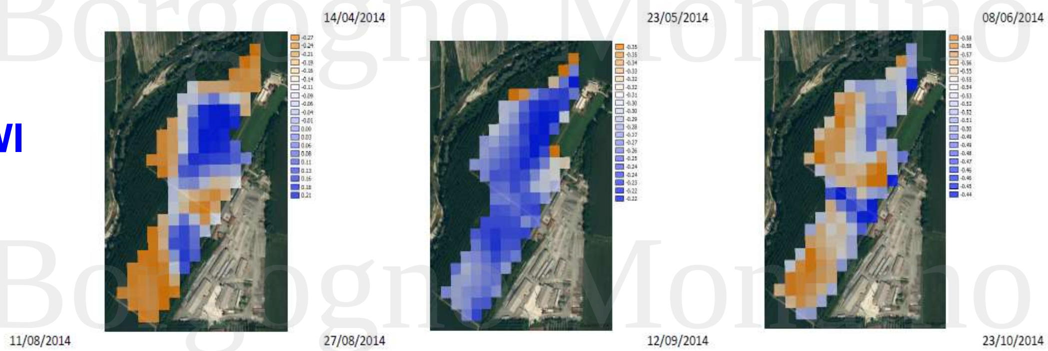
SPECTRAL INDICES
WATER CONTENT

NORMALIZED DIFFERENCE WATER INDEX

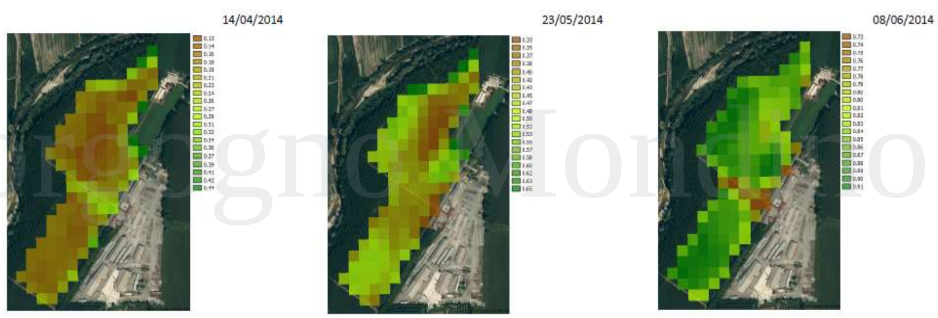
$$NDWI = \frac{NIR - MIR1/2}{NIR + MIR1/2}$$

NDWI is ordinarily related to surface water content. Its meaning (therefore its value) depends on the explored cover type. Higher is NDWI value, higher the water content. Its interpretation cannot be given without taking care about stability of observed surface.

NDWI



NDVI



In SPACE DOMAIN it defines the relative water content of pixels within a patch that is known to host the same land cover type

In TIME DOMAIN variations are significant only if the pixel does not change its nature (e.g. during transitional phase of crop growing variations in time are not significant)

In this case, NDVI can be used to test stability of crop.

A time series of NDWI over changing areas ha NO MEANING and can drive to COMPLETELY WRONG CONCLUSIONS.

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SPECTRAL INDICES

Index		Formula	Estimated Parameter
NDVI	Normalized Difference Vegetation Index	$\frac{\rho_{NIR}-\rho_{RED}}{\rho_{NIR}+\rho_{RED}}$	LAI
SR	Simple Ratio Index	$\frac{\rho_{NIR}}{\rho_{RED}}$	LAI
PVI	Perpendicular Vegetation Index	$\sqrt{(\rho_{NIR\_soil}-\rho_{NIR\_vege})^2+(\rho_{NIR\_soil}-\rho_{NIR\_vege})^2}$	LAI
MTVI	Modified Triangular Vegetation Index	$1.2\cdot[1.2\cdot(\rho_{800}-\rho_{550})-2.5\cdot(\rho_{670}-\rho_{550})]$	LAI
RDVI	Renormalized Difference Vegetation Index	$\frac{\rho_{N800}-\rho_{670}}{\sqrt{\rho_{800}+\rho_{670}}}$	PAR
TVI	Triangular Vegetation Index	$0.5\cdot[120\cdot(\rho_{750}-\rho_{550})-200\cdot(\rho_{670}-\rho_{550})]$	LAI
OSAVI	Optimized Soil Adjusted Vegetation Index	$(1+0.16)\cdot\frac{\rho_{800}-\rho_{670}}{\rho_{800}+\rho_{670}+0.16}$	Leaf Chlorophyll Content

Index		Formula	Estimated Parameter
MCARI	Modified Chlorophhyll Absorption in Reflectance Index	$[(\rho_{700}-\rho_{670})-0.2\cdot(\rho_{700}-\rho_{550})]\cdot\frac{\rho_{700}}{\rho_{670}}$	Leaf Chlorophyll Content
TCARI	Transformed Chlorophhyll Absorption in Reflectance Index	$3\cdot[(\rho_{700}-\rho_{670})-0.2\cdot(\rho_{700}-\rho_{550})]\cdot\frac{\rho_{700}}{\rho_{670}}$	Leaf Chlorophyll Content
ZM	Zarco-Miller	$\frac{\rho_{750}}{\rho_{710}}$	Leaf Chlorophyll Content
PRI	Photochemical Reflectance Index	$\frac{\rho_{531}-\rho_{570}}{\rho_{531}+\rho_{570}}$	Efficenza fotosintetica
RGI, BGI, BRI	Blue, Red, Green Indices	$\frac{\rho_{690}}{\rho_{550}};\frac{\rho_{400}}{\rho_{550}};\frac{\rho_{400}}{\rho_{690}}$	Leaf Chlorophyll Content
WDRVI	Wide Dynamic Range Vegetation Index	$\frac{a\cdot\rho_{NIR}-\rho_{RED}}{a\cdot\rho_{NIR}+\rho_{RED}}$	LAI

SPECTRAL INDICES

Index		Formula	Estimated Parameter
SIPI	Structure-Intensive Pigment Index	(ρ800–ρ450)/(ρ800+ρ650)	carotenoids
	Gitelson Car	[ρ(510–520)^–1–ρ(540–560)^–1]*ρ(760–800)	carotenoids
SR	Blackburn Car	(ρ800–ρ470)/(ρ800+ρ470)	carotenoids
	Gitelson Anth	[ρ(540–560)^–1–ρ(690–710)^–1]*ρ(760–800)	carotenoids

Indice		Formula	Parametro stimato
NDWI	Normalized Difference Water Index	(ρ860–ρ1240)/(ρ860+ρ1240)	Vegetation liquid water changes
NDII	Normalized Difference Infrared Index	(ρ850–ρ1650)/(ρ850+ρ4650)	Leaf equivalent water thickness

SPECTRAL INDICES- ONLINE DATBASES

https://www.indexdatabase.de/search/?s=NDVI

Index DataBase

A database for remote sensing indices

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IDB

Search results for »NDVI«

- 27 Indices
- 8 References

Indices

Nr	Name	Abbrev.	Formula	Variables
1	Atmospherically Resistant Vegetation Index	ARVI	$\frac{NIR-RED-y(RED-BLUE)}{NIR+RED-y(RED-BLUE)}$	NIR = [781:1399]
2	Atmospherically Resistant Vegetation Index 2	ARVI2	$-0.18+1.17\left(\frac{NIR-RED}{NIR+RED}\right)$	
3	CASI NDVI	CASI NDVI	$\frac{([770:780]+[784:790])-([655:665]+[676:685])}{([770:780]+[784:790])+([655:665]+[676:685])}$	
4	Crop water stress index	CWSI	$\frac{C-A}{B-A}$	
5	Green Normalized Difference Vegetation Index	GNDVI	$\frac{NIR-[540:570]}{NIR+[540:570]}$	
6	Green-Blue NDVI	GBNDVI	$\frac{NIR-(GREEN+BLUE)}{NIR+(GREEN+BLUE)}$	
7	Green-Red NDVI	GRNDVI	$\frac{NIR-(GREEN+RED)}{NIR+(GREEN+RED)}$	
8	Modified NDVI	mNDVI	$\frac{800nm-680nm}{800nm+680nm-2445nm}$	
9	Normalized Difference 750/550 Green NDVI	NDVIg	$\frac{750nm-550nm}{750nm+550nm}$	
10	Normalized Difference 750/650	NDVI750/650	$\frac{750nm-650nm}{750nm+650nm}$	
11	Normalized Difference 750/705 Chl NDI	NDVI705	$\frac{750nm-705nm}{750nm+705nm}$	

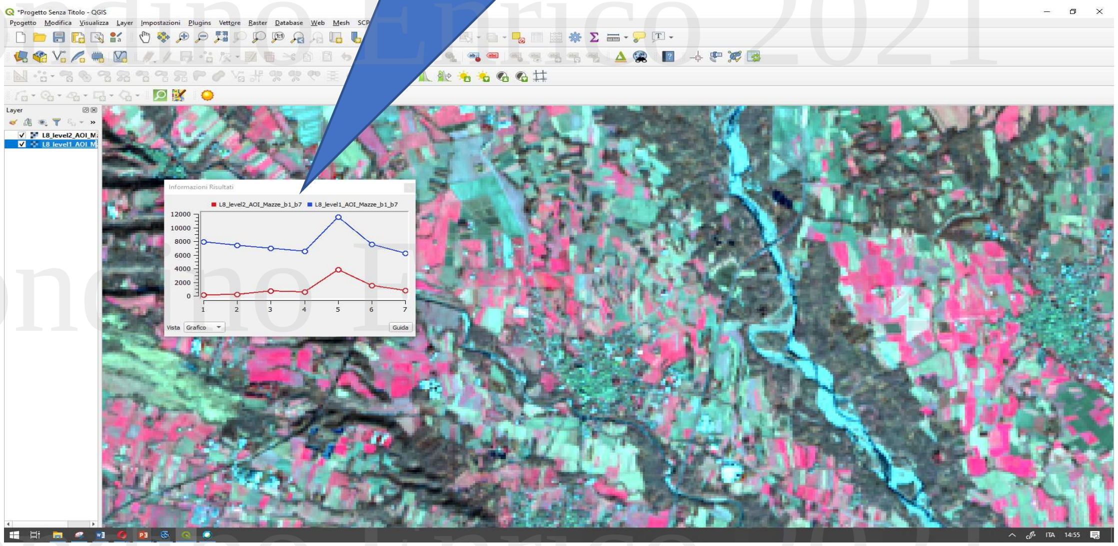
What about working with no IMAGE calibration?

RESULTS ARE DIFFERENT since CALIBRATION COEFFICIENTS, BACKSCATTERING AND ATMOSPHERE TRANSMISSIVITY TERMS depends on BAND and ACQUISITION DATE/TIME.

Spectral indices, built as normalized RATIOS, can reduce difference. Nevertheless, some test done on satellite imagery proved that:

1. NDVI values from NOT CALIBRATED data is often UNDERESTIMATED (- 0.2, 0.3 NDVI points)
2. Correlation (Pearson's r) between NDVI temporal profiles from calibrated and not calibrated images varies between 0.5 and 0.95 depending on the pixel.
3. Temporal comparisons from not calibrated data are not reliable at all.

Spectral signatures of the same pixel from calibrated (red) an not calibrated Landsat image



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SPECTRAL INDICES

Exploring vegetation phenology - temporal profiles and metrics

2 MAIN APPROACHES ARE EXPECTED

A) If the analysis just involves two time stages, i.e. AFTER – BEFORE, the approach is called **CHANGE DETECTION.** This approach is typical of analyses concerning geometric variations of land cover patches. It generally involves TWO CLASSIFICATIONS. Expected results are a quantification of changes (e.g. ha), a contingency matrix defining migration of classes and a map of occurred changes. INPUT data are, in general, 2 multispectral images properly selected, that permit to classify accurately land cover classes.

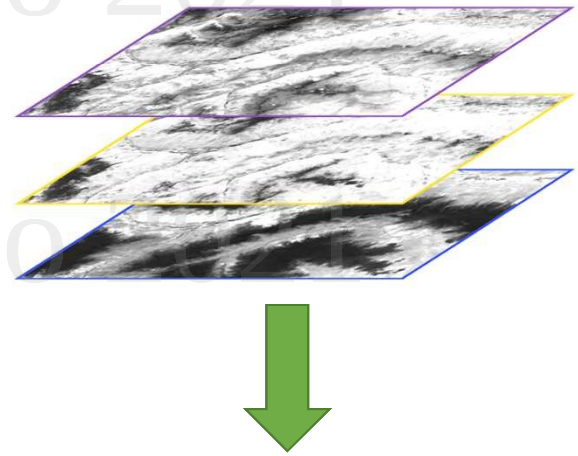
B) If the analysis is somehow continuous, tending to a monitoring approach, we more properly have to define it as **MULTITEMPORAL ANALYSIS.** The latter requires that the data to base deductions on are TIME SERIES of images, i.e. stacks of bands, indices, classifications organized in a chronological way to cover the reference period. In general, deductions are based on the joint interpretation of many sequential observations, having a proper time frequency. The observation period depends on the application: for example, precision farming generally require that an entire year is sampled and the correspondent image time series analysed to represent phenology of crops, or evapotranspiration seasonality, etc. Differently, climate change related effects are expected to be perceived along a wider time series covering some decades. INPUT data are, generally, time series of spectral indices maps, that are able to summarize the spectral content of a whole spectrum useful for the specific application we're facing (e.g. VI for phenology) . Sometimes, analysis can rely on maps of estimates of a bio-physical parameter obtained by statistical (or machine learning) inference from remotely sensed images or derived indices (e.g. Evapotranspiration, GPP, FAPAR, LAI, etc.)

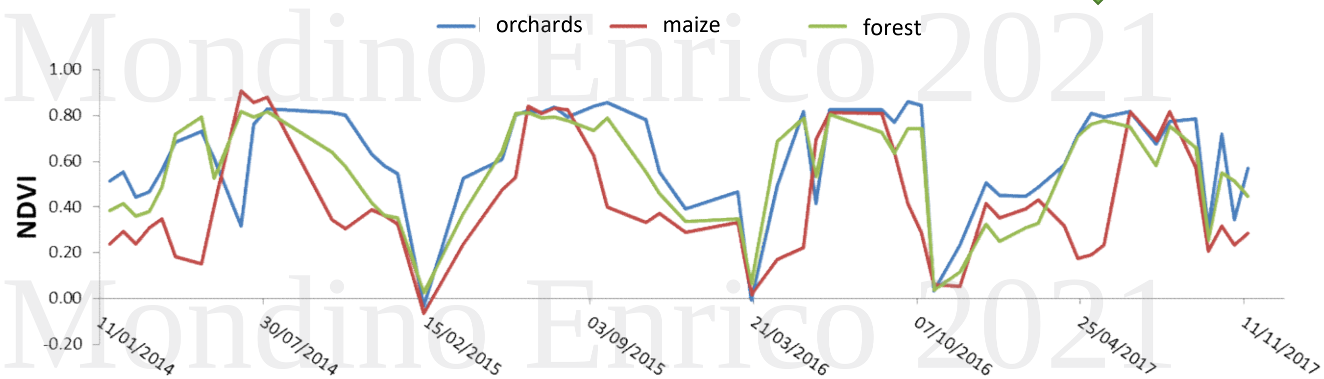
SPECTRAL INDICES TIME SERIES

If acquisitions of the same area are recurrent (e.g. satellite missions) a spectral index map can be computed for each passage. Consequently a time series (temporal stack) of index maps can be generated.

If the spectral index is a vegetation one, related time series can be used to interpret plant/crops phenology.

If time series include more years, yearly profiles can be compared and used to address proper management actions





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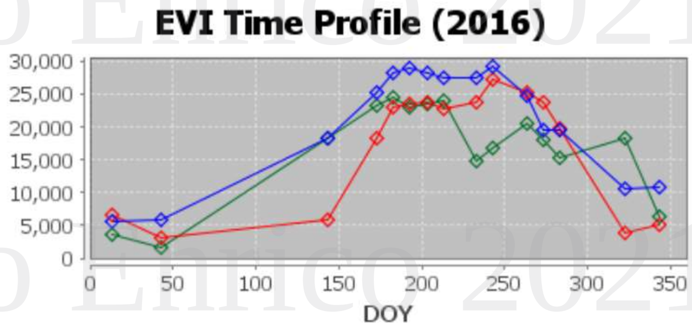
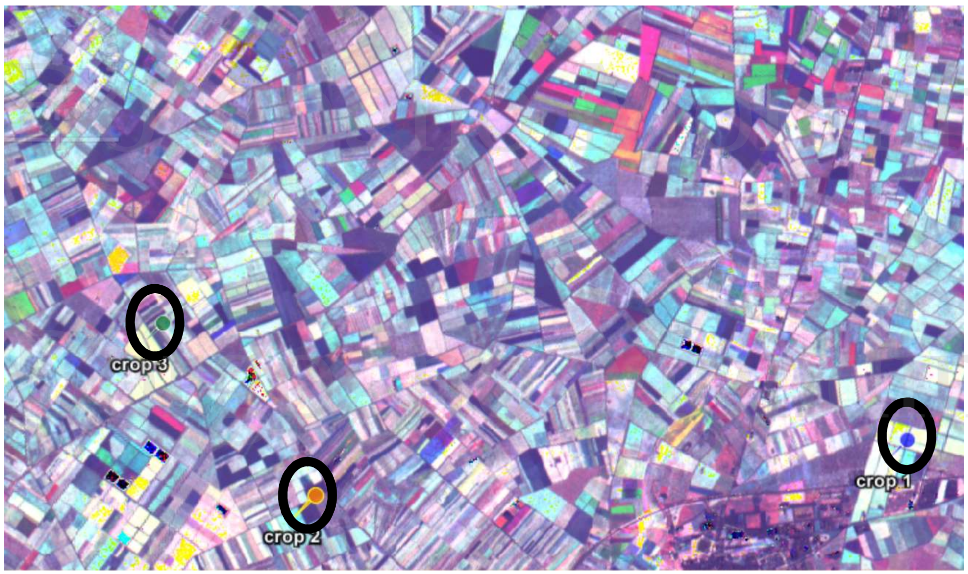
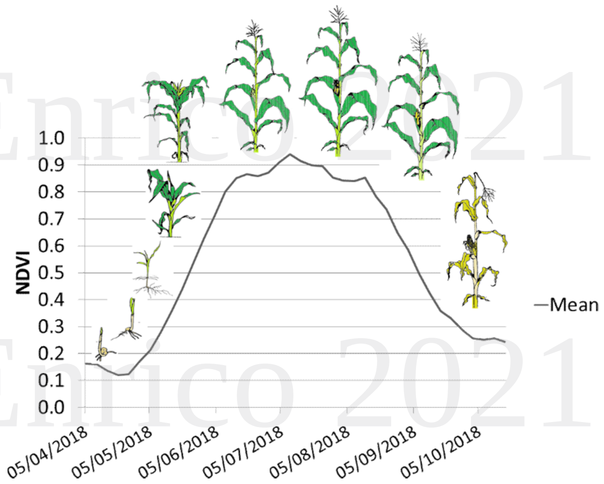
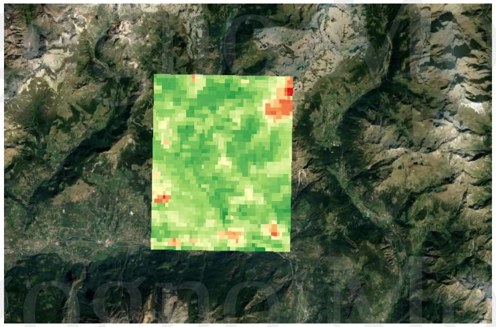
MONITORING CROPS



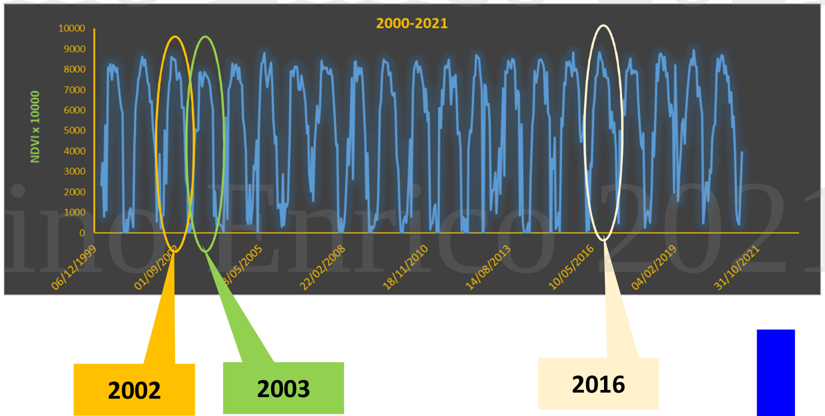




SPECTRAL INDICES TIME SERIES

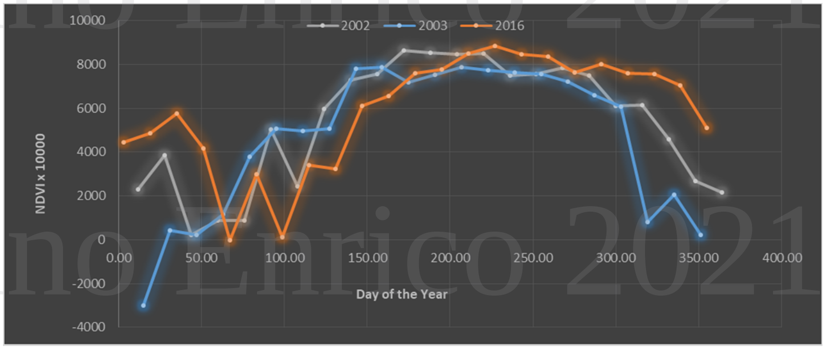


Multi-year Time Series (1 pixel temporal profile) → MOD13Q1 (TERRA MODIS product)



	2002			2003			2016	
Date	DOY	NDVI	Date	DOY	NDVI	Date	DOY	NDVI
13/01/2002	12.00	2309	16/01/2003	15	-3000	04/01/2016	3	4434
29/01/2002	28.00	3863	01/02/2003	31	433	20/01/2016	19	4854
14/02/2002	44.00	214	17/02/2003	47	205	05/02/2016	35	5764
02/03/2002	60.00	874	05/03/2003	63	1140	21/02/2016	51	4171
18/03/2002	76.00	891	21/03/2003	79	3800	08/03/2016	67	-13
03/04/2002	92.00	5024	06/04/2003	95	5086	24/03/2016	83	3007
19/04/2002	108.00	2427	22/04/2003	111	4977	09/04/2016	99	124
05/05/2002	124.00	5969	08/05/2003	127	5062	25/04/2016	115	3392
21/05/2002	140.00	7278	24/05/2003	143	7818	11/05/2016	131	3252
06/06/2002	156.00	7573	09/06/2003	159	7887	27/05/2016	147	6093
22/06/2002	172.00	8633	25/06/2003	175	7171	12/06/2016	163	6547
08/07/2002	188.00	8544	11/07/2003	191	7520	28/06/2016	179	7607
24/07/2002	204.00	8468	27/07/2003	207	7869	14/07/2016	195	7779
09/08/2002	220.00	8497	12/08/2003	223	7734	30/07/2016	211	8510
25/08/2002	236.00	7487	28/08/2003	239	7630	15/08/2016	227	8847
10/09/2002	252.00	7567	13/09/2003	255	7554	31/08/2016	243	8481
26/09/2002	268.00	7852	29/09/2003	271	7229	16/09/2016	259	8372
12/10/2002	284.00	7488	15/10/2003	287	6605	02/10/2016	275	7650
28/10/2002	300.00	6125	31/10/2003	303	6067	18/10/2016	291	8021
13/11/2002	316.00	6156	16/11/2003	319	812	03/11/2016	307	7610
29/11/2002	332.00	4581	02/12/2003	335	2045	19/11/2016	323	7569
15/12/2002	348.00	2664	18/12/2003	351	206	05/12/2016	339	7030
31/12/2002	364.00	2150				21/12/2016	355	5115

Comparing yearly phenology at different years



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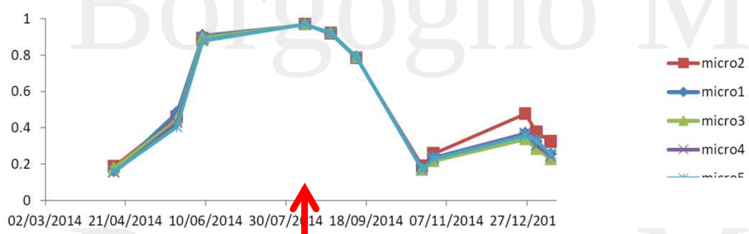
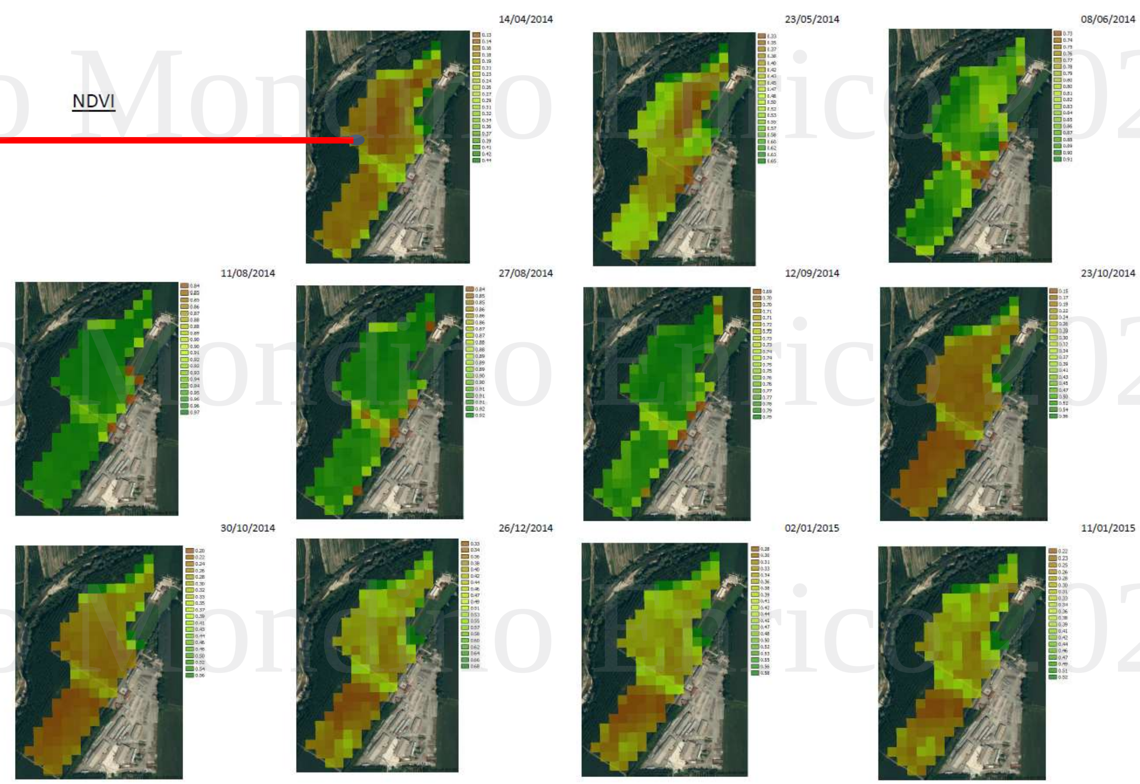
SPECTRAL INDICES TIME SERIES



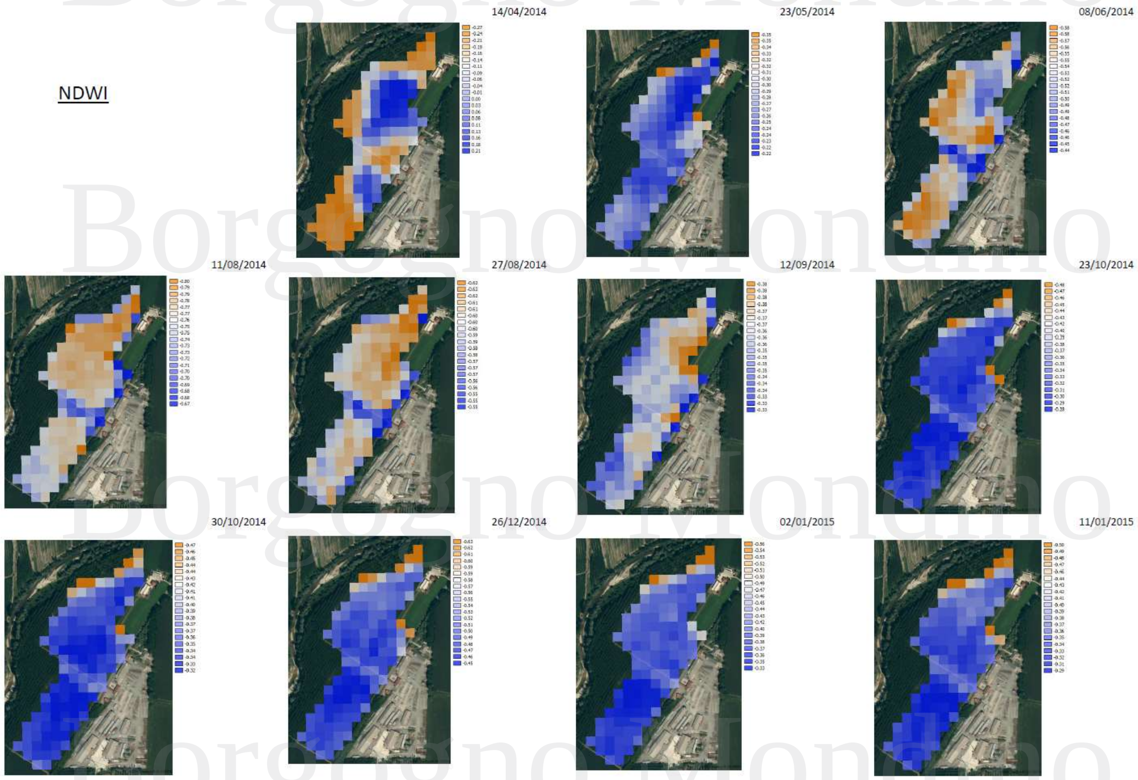
$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

NDVI



SPECTRAL INDICES TIME SERIES

NDWI

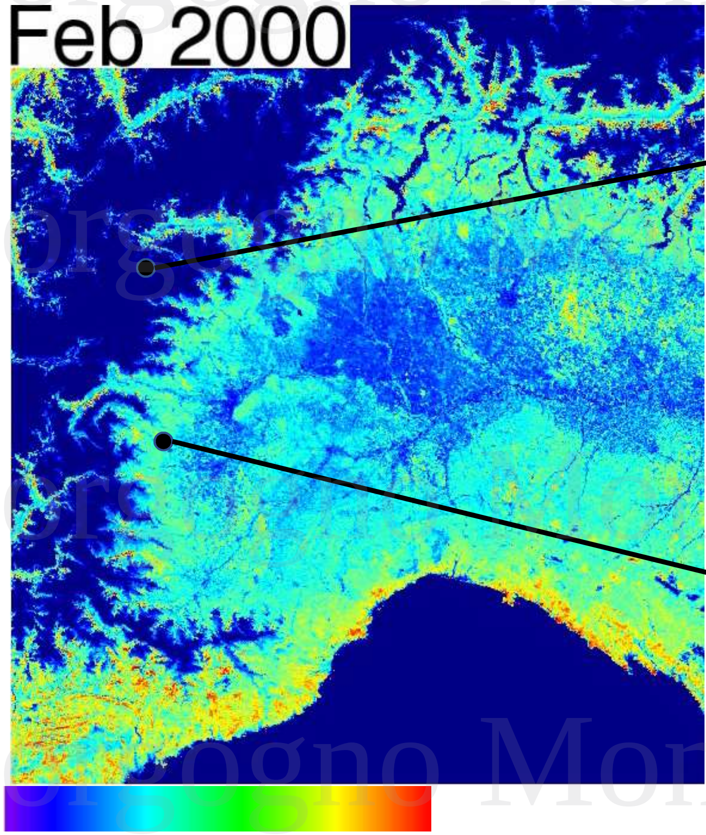


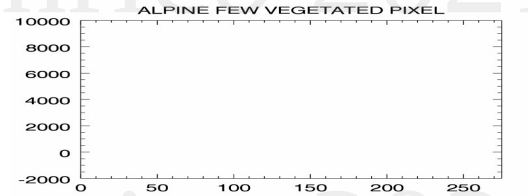
Not all the spectral indices can be opportunely read along time series! Reasonability of the approach has to be carefully considered.

Indices used to explore «relative» water quantity differences have to be interpreted admitting that observed surfaces are not changing (in type) spatially and temporally.

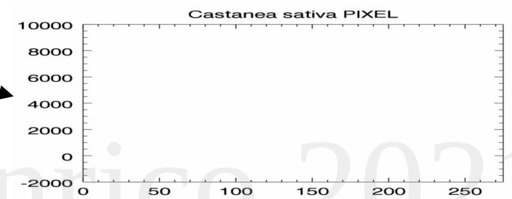
E.g. a crop field monitored along its growing season cannot give any information about temporal trend of water content since pixels are changing their innest nature while crop develops. Only at a mature stage this is achievable.

NDVI MAP TIME SERIES





$$NDVI = \frac{NIR - RED}{NIR + RED}$$



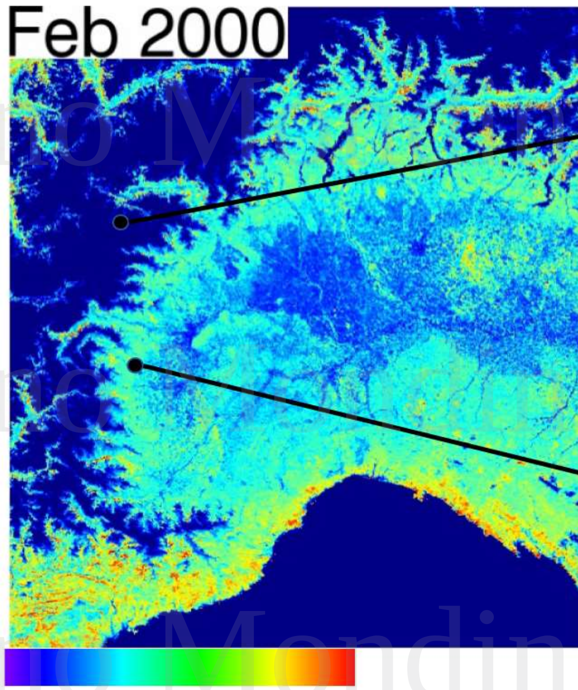
X axis: time (DOY)

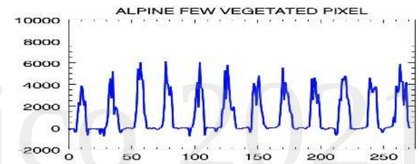
Y axis: NDVI(t)

Sampled NDVI Temporal Profiles

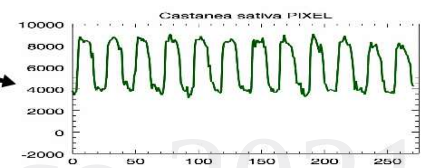
Sampled NDVI Temporal Profiles

NDVI Map Time Series





$$NDVI = \frac{NIR - RED}{NIR + RED}$$



X axis: time (DOY)

Y axis: NDVI(t)

SENSITIVITY (PRECISION) OF SPECTRAL INDICES

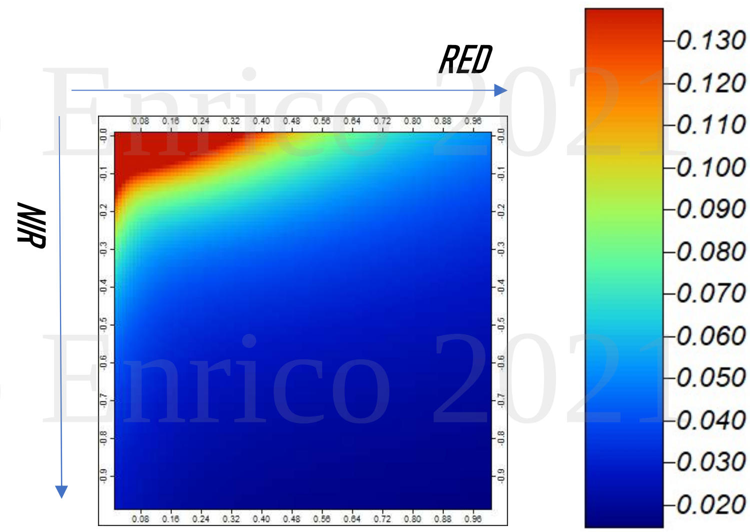
Which VI differences are significant ? It depends on the calibration quality of involved bands.
VI is an indirect measure and, consequqntly, it absorbs all errors from partecipating players (i.e. at-the ground reflectance of involved bands)

An estimate of VI precision can be obtained by applying the Variance Propagation Law to its formula, once precision of reflectance measures is known.

With reference to NDVI:

$$\sigma_{NDVI} = \sqrt{\left[\frac{2\cdot\rho_{RED}}{(\rho_{NIR}+\rho_{RED})^2}\right]^2\cdot\sigma_{NIR}^2 + \left[\frac{2\cdot\rho_{NIR}}{(\rho_{NIR}+\rho_{RED})^2}\right]^2\cdot\sigma_{RED}^2}$$

If σ_{NIR} = 0.026 and σ_{RED}= 0.013 (Sentinel 2 L2A product) →



A significant difference is the one having a value greater than the expected precision for its measurement. This is true for VI differences in TIME and SPACE DOMAIN

Expected precision ? → $\sqrt{\sigma_{NDVI1}^2 + \sigma_{NDVI2}^2}$

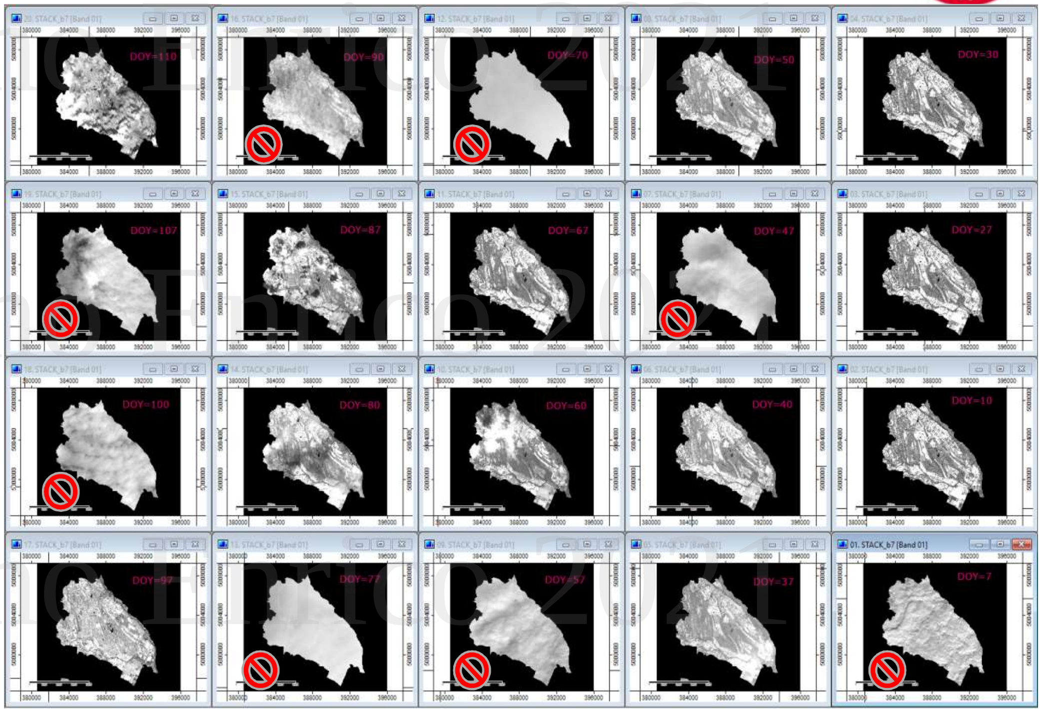
PROCESSING OF SPECTRAL INDICES TIME SERIES

Nominal time resolution is drastically reduced by clouds. Clouds are mapped during data preparation and derived maps made available for users. When composing a time series

a) the first task is to operate a selection of «good» observations, masking out the bad ones;

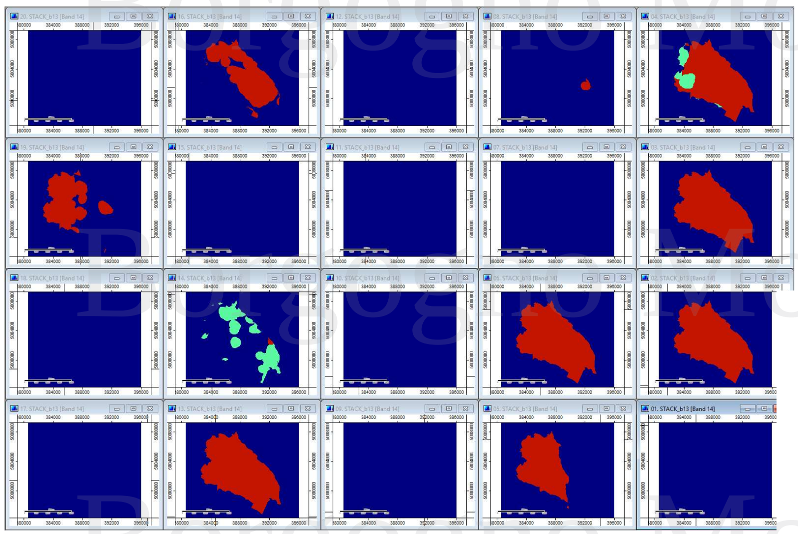
b) An interpolation and regularization step is required to fill the gaps generated at the previous stage;

c) a further filtering is expected to smooth local (but «good») sudden variations possibly due to specific situations like snow falls, floods or residual uncorrected observations that were not possible to mask out as «bad» observations.



MASKING OUT «BAD» OBSERVATIONS

Data coming from Scientific HUB (archives) like those from NASA/USGS and Copernicus/ESA are in general supplied together with auxiliary layers where flags are mapped to indicate class and quality of pixels. Consequently, every pixel at whatever date is known to be a "good" or "bad" pixel. One can decode if using it when composing the local temporal profile. → E.g. Sentinel 2 Level 2A data are supplied together with a **CLASSIFICATION and a QUALITY LAYER (SCL, QI)** that makes possible to recognize pixels of interest over the scene.

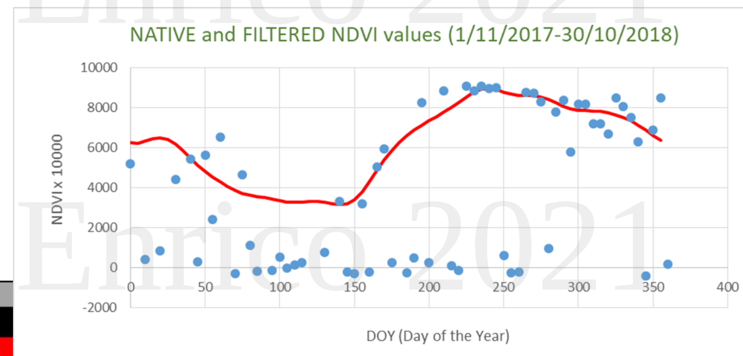


QUALITY LAYER TIME SERIES (0 = "good" observations)

Label	Classification
0	NO_DATA
1	SATURATED_OR_DEFECTIVE
2	DARK_AREA_PIXELS
3	CLOUD_SHADOWS
4	VEGETATION
5	NOT_VEGETATED
6	WATER
7	UNCLASSIFIED
8	CLOUD_MEDIUM_PROBABILITY
9	CLOUD_HIGH_PROBABILITY
10	THIN_CIRRUS
11	SNOW

Figure 3: Scene Classification Values

SCL CODES ("good" = 2,3,4,5,6,7,11 - "bad" = 0,1,8,9,10)



Temporal profile of a vegetated pixel. Points are native observations, red is the filtered profile after "bad" observations removal, interpolation and filtering

FILLING THE GAPS IN TEMPORAL PROFILES

Once «bad» observations have been removed with reference to auxiliary data, an interpolating step is required to fill the remaining GAPs before proceeding to interpret profiles.

Profiles can be interpolated adopting many approaches but two processing stages can be recognized.
1- One aimed at filling the gap and possibly regularizing profiles (estimating new VI values at regularly spaced dates);
2- One aimed at simplifying the regularized (or not, depending on the model) profile fitting the dominant trend with functions typically shaped like bells.

Regularization (1) can be obtained

a) by 1°, 2° or 3° order polynomials (LINEAR)
b) by spline-based models

A filtering step (Savitzky-Golay, convolution) can be also associated to this processing phase (after or before)

2 can be operated with reference to

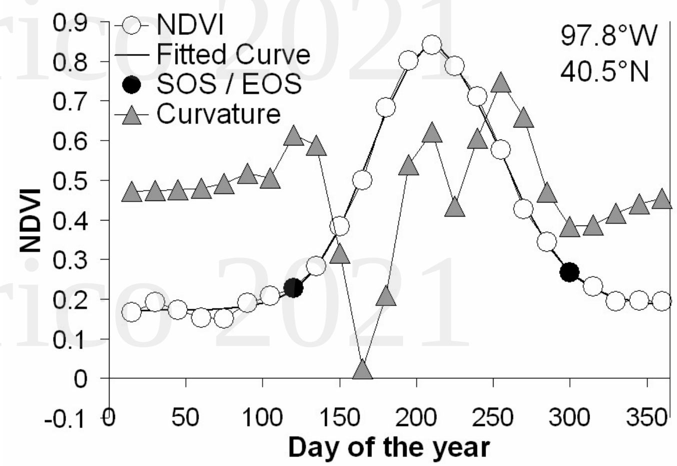
a) bell-shaped fitting models (LOGISTIC, DOUBLE LOGISTIC, GAUSSIAN, etc.)
b) FFT (Fast Fourier Transform) to retain only low frequency components

FILLING THE GAPS IN TEMPORAL PROFILES

Logistic Model

- Straightforward logistic model
- *a* and *b* are empirical coefficients that are associated with the timing and rate of change in VI.
- The term *c+d* give the potential maximum VI value
- *d* represents the minimum value (the background EVI value).

$$VI(t) = \frac{c}{1 + e^{a+bt}} + d$$



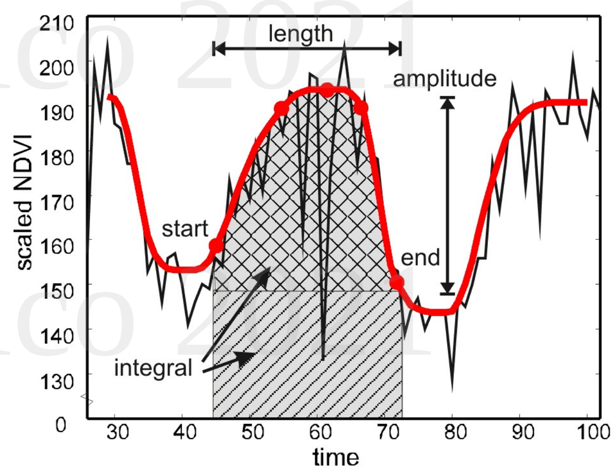
Zhang, 2004

Gaussian Local Functions

The upper part of the equation is fitted to the right half of the time series. The lower part of the equation fits to the left half of the time series.

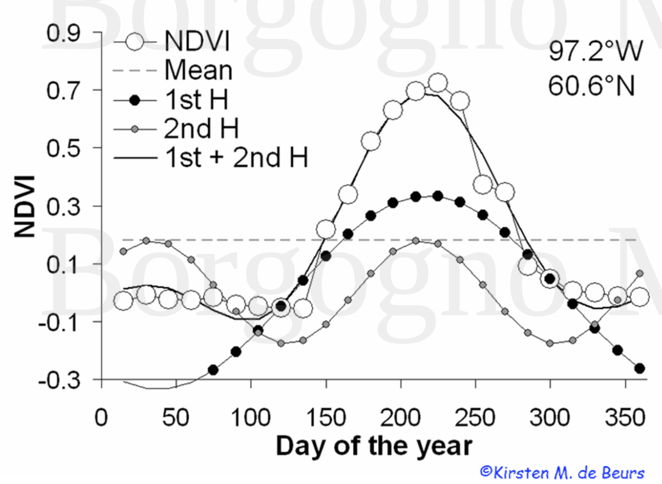
a2 and *a4*: the width of the curves ; *a3* and *a5*: the flatness (or kurtosis) of the curves; c1 and c2: base parameters determine the intercept and the amplitude of the curves, respectively. a1: the timing of the maximum (measured in time units).

$$VI(t) = c_1 + c_2 \cdot \begin{Bmatrix} e^{-\left(\frac{t-a_1}{a_2}\right)^{a_3}} & if\ t > a_1 \\ e^{-\left(\frac{a_1-t}{a_4}\right)^{a_5}} & if\ t < a_1 \end{Bmatrix}$$



FITTING PROFILES WITH BELL-SHAPED MODELS

FFT



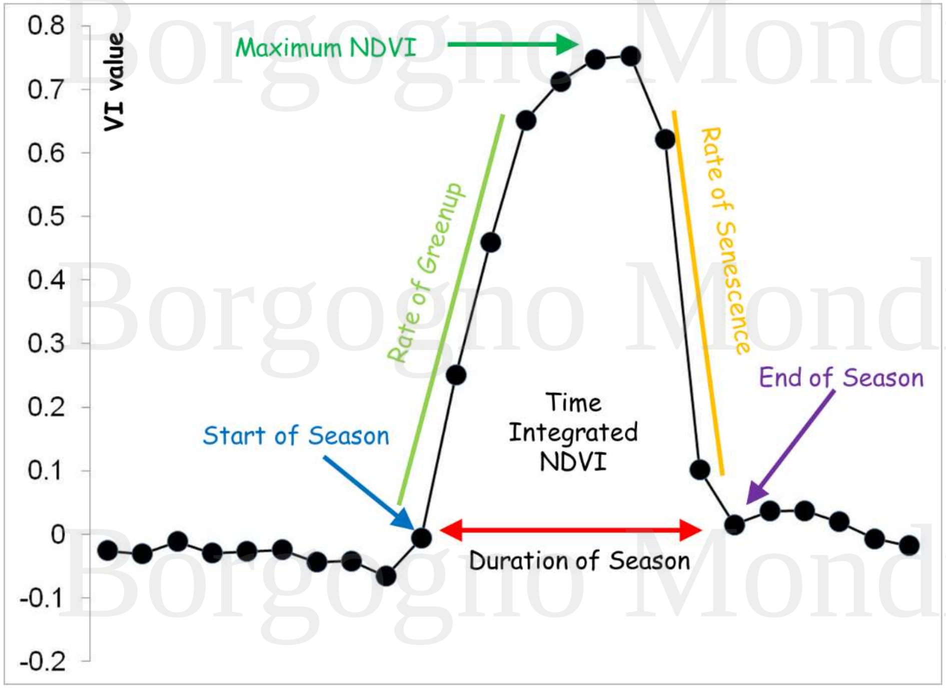
FFT (FAST FOURIER TRANSFORM) can be operated only for REGULARLY SPACED DATA.

FFT decomposes a complex signal, possibly periodic, into a sum of multiple sine and cosine functions each characterized by a frequency and amplitude. High frequency components describe local and sudden profile variations; low frequency components describe slow and seasonal components. Once the spectrum of all possible components (the number depend on the number of observations)

SYNTHESIZING VI TEMPORAL PROFILES
PHENOLOGICAL METRICS

Once the profile has been modelled/filtered some METRICS can be obtained and used to explore eventual trends in phenology along a wide time range.

Phenological metrics are numerical parameters that can be used to synthesize phenology of vegetation. A temporal profile of a vegetation index (VI) can be used as representative of vegetation phenology. Consequently, for each vegetated pixel of a VI image time series, we can derive information about its phenology at year and multi-year level.



- **Date of SOS/EOS:** day of the year (DOY) when the phenolgical season starts (SOS) or ends (EOS)
- **Length/Duration of Season (LOS):** EOS-SOS difference (days)
- **Date of MAX VI :** day of the year (DOY) when VI is maximum.
- **Maximum VI**
- **VI@SOS** and **VI@EOS :** VI value at SOS and EOS
- **VI seasonal integral:** total vegetative activity within SOS and EOS (VI sum)
- **Rate of Greenup and Rate of Senescence:** speed of greening increasing (@SOS) or decreasing (@EOS)

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APPROACHES FOR PM ESTIMATE

A diversity of satellite measures and methods has been developed. Methods can be divided into 2 main categories:

- Threshold-based Methods
- Derivative-based Methods

A search range in the time domain has to be set to avoid problems related to multiple phenological cycles along the year

Threshold-based Methods (ABSOLUTE)

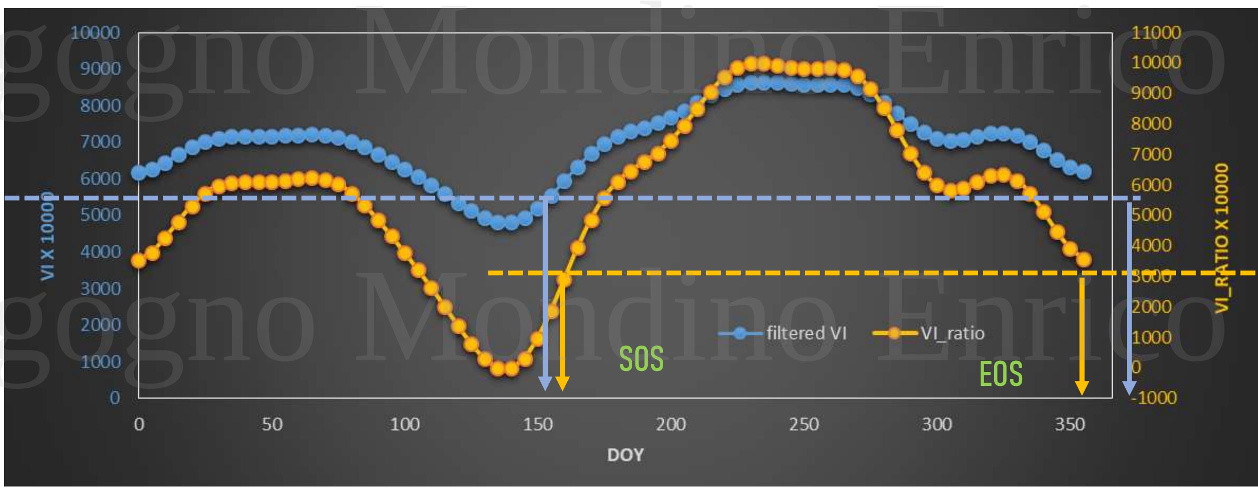
- It's the simplest method to determine SOS and EOS.
- Threshold is arbitrarily set at a certain VI value (e.g. 0.3, 0.4, 0.5 etc).

Threshold-based Methods (RELATIVE)

NDVI is translated to a ratio based on the yearly minimum and maximum

$$NDVI_{ratio} = \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDV_{max})}$$

VI = 0.55

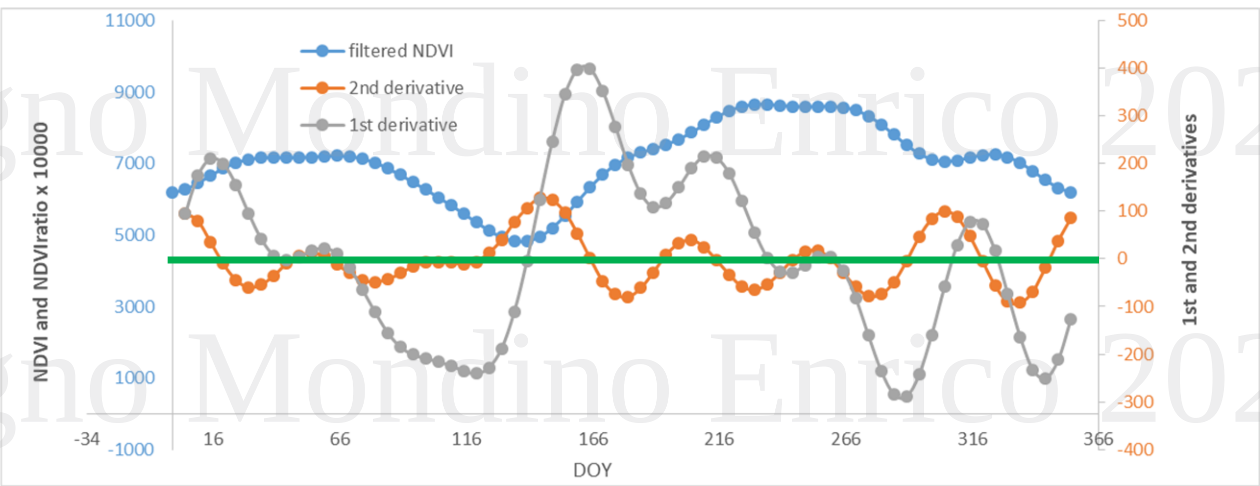


Ratio = 0.3

1st / 2nd derivative-based Methods (ABSOLUTE)

Derivative maxima/minima/zeroes of a continuous function define objective geometrical conditions of a curve, related to its steepness (1st derivative), concavity (2nd derivative) or singular points.
Main PM can somehow be associated to these peculiar points of a function. Derivative can be computed in an analytical way if the profile was fitted by a function (like Gaussian, Logistic or Double Logistic) or computed by a numerical approach based on finite differences.

To be effective, this approach needs that fitting curves are monotonic in both the ascending and descending traits. Otherwise, local minima/maxima can compromise results.



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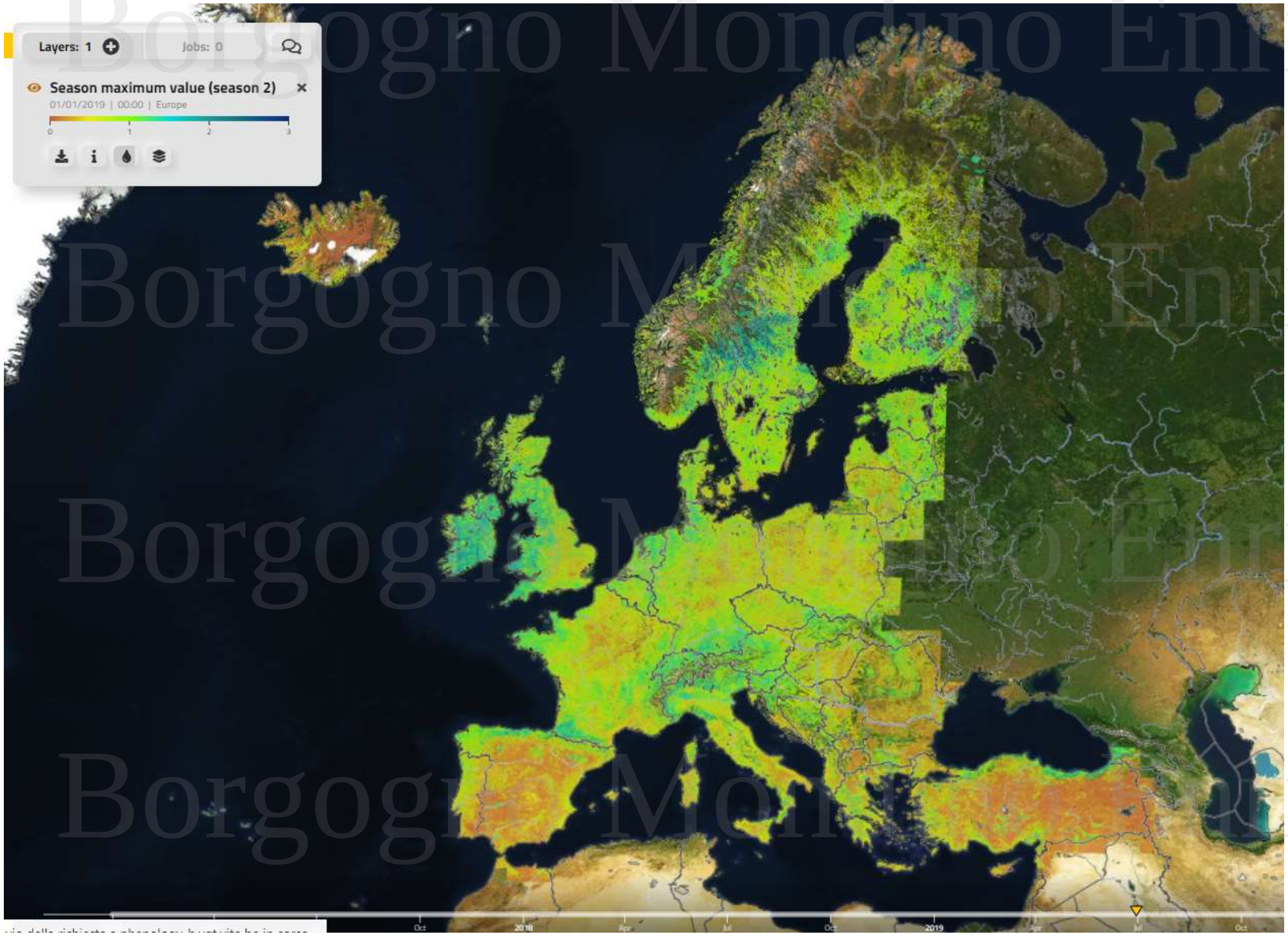
The COPERNICUS **HR-VPP** (High resolution – Vegetation Phenology and Productivity) Product



	Phenological Metric (from PPI trajectories)
1	Amplitude (season 1/2/2)
2	End-of-season date (season 1/2)
3	End-of-season value (season 1/2)
4	Season length (season 1/2) days
5	Season maximum date (season 1/2)
6	Season maximum value (season 1/2)
7	Season minimum value (season 1/2)
8	Seasonal productivity (season 1/2) PPI·day
9	Slope of green-down period (season 1/2) PPI/day
10	Slope of green-up period (season 1/2) PPI/day
11	Start-of-season date (season 1/2)
12	Start-of-season value (season 1/2)
13	Total productivity (season 1/2) PPI·day

The COPERNICUS HR-VPP (High resolution – Vegetation Phenology and Productivity) Product

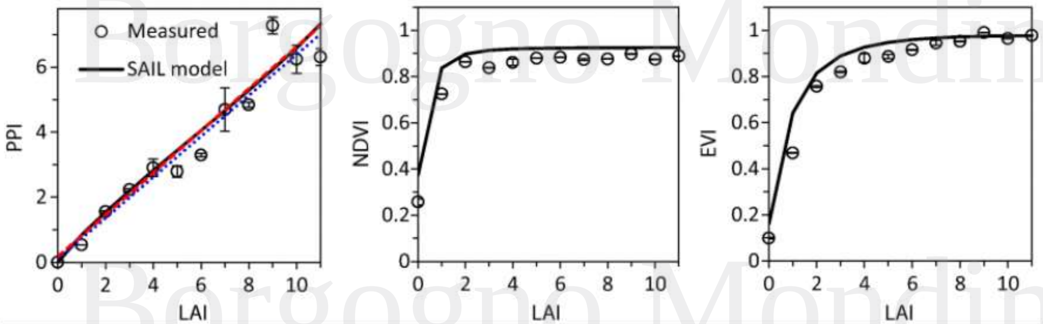


Fig. 6 from Jin and Eklundh (2014).The figure shows linearity of PPI with leaf area index (LAI) (left), in comparison with NDVI (center) and EVI (right). Lines are model data and circles are measurements.

This figure shows that PPI is minimally affected by snow:

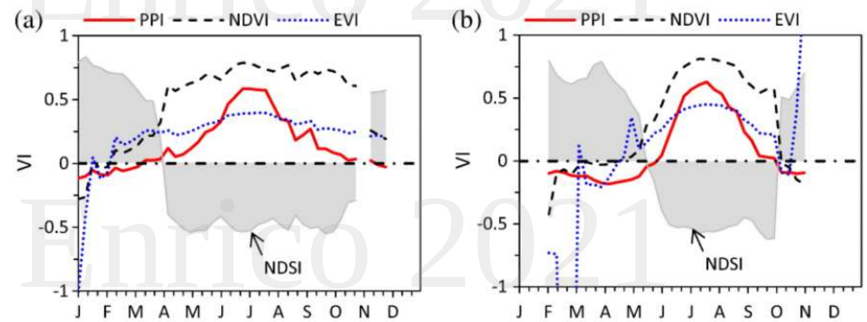


Fig. 10 from Jin and Eklundh (2014). The figure shows time series of PPI (red) in comparison to the NDSI snow index, and the indices NDVI and EVI. Note the smoothness of PPI at the ends and beginnings of the snow seasons. The left figure shows data from t

This figure shows that PPI is strongly related to coniferous GPP, estimated with carbon flux data:

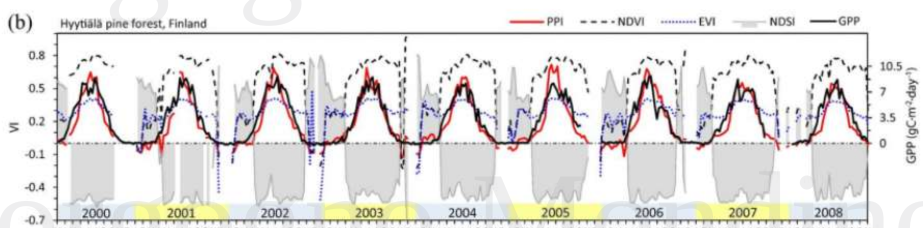


Fig. 11b from Jin and Eklundh (2014). The figure shows time series of PPI (red) in comparison with eddy-covariance measured GPP (black), and the indices NDVI and EVI at the Hyytiälä pine forest.

Phenological Metrics are computed with reference to the PPI (Plant Phenology Index).

Hongxiao Jin, Lars Eklundh, A physically based vegetation index for improved monitoring of plant phenology, Remote Sensing of Environment, Volume 152, 2014, Pages 512-525, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2014.07.010.

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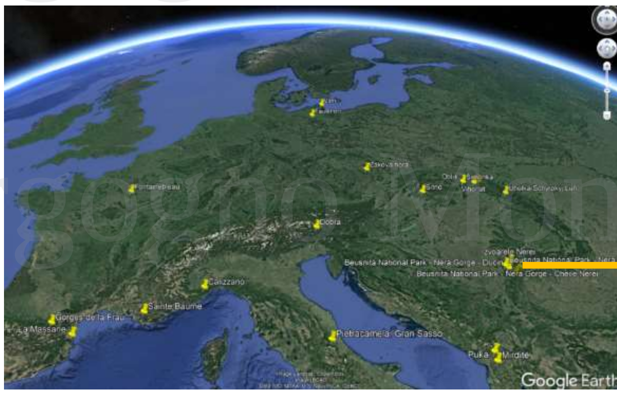
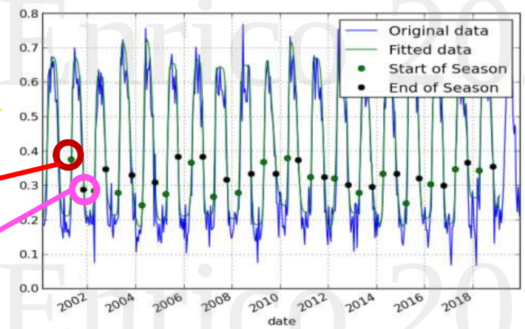
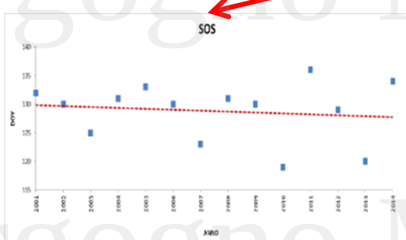
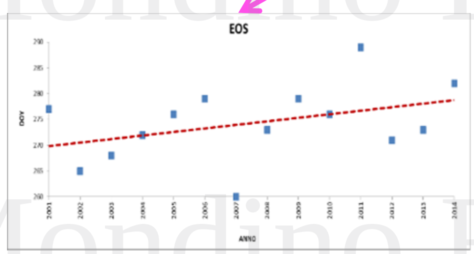
EXPLORING THE LOCAL TREND OF PHENOLOGICAL METRICS ALONG TIME

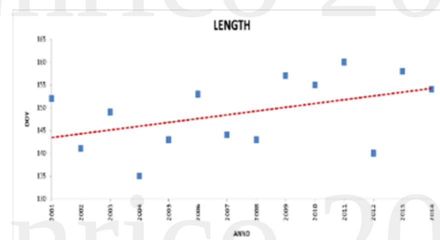


PM trends over wide time range makes possible to test Climate Change effects on vegetation and mapping the strength/velocity of variations) (eg. European Beech Forests)

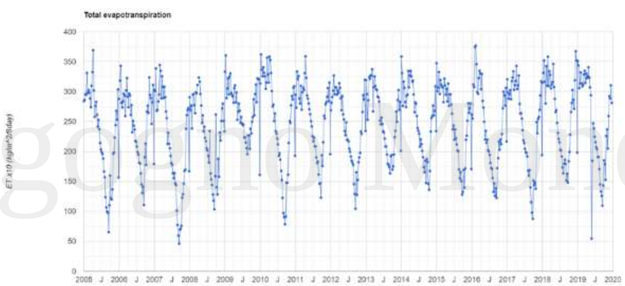








Exploring Changes of Biophysical Parameters that Spectral Indices are Predictor for



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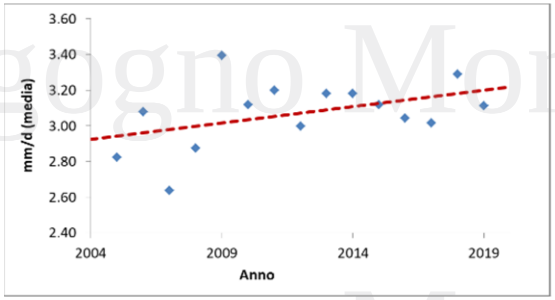
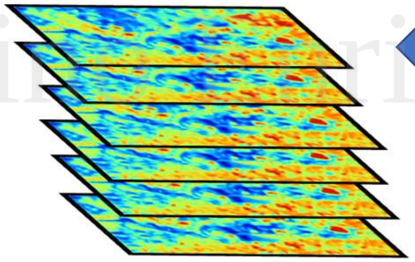


→ trend ? Significant or Not?

ET maps from MOD16

time



$$\lambda ET = \frac{\Delta(R_n - G) + \rho_a \cdot c_p \frac{(e_s - e_a)}{r_a}}{\Delta + \gamma(1 + \frac{r_s}{r_a})}$$

Meteo data